INVESTIGATION ON BRAIN TUMOUR SEGMENTATION AND CLASSIFICATION USING IMPROVED INTERACTIVE MACHINE LEARNING AND DEEP LEARNING APPROACHES

A SYNOPSIS

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1. INTRODUCTION

A tumor is a medical term for abnormal cell growth inside the brain. Brain tumors in the human body comprise a diverse group of neoplasms that vary in their behavior depending on various factors, such as the cell of origin, site of occurrence, morphology, and pattern of spread. The human brain is the most sensitive part of the body, which controls muscle movements and interprets sensory information like sight, sound, touch, taste, pain, etc. Any tumor can affect such sensory details and muscle movements or even result in more hazardous situations, including loss of life. Since the position of the tumor is not designated, it can occur in any part of the brain. Depending upon the place of origination, the tumor can be categorized into primary and secondary tumors. If the tumor has originated inside the skull, it is known as a primary brain tumor [1]. otherwise, if the tumor's origination point is somewhere else in the body and has later moved to the brain, such tumors are called secondary tumors.

Brain diseases are mostly caused by the abnormal growth of brain cells, which directly damage the brain structure and lead to brain cancer. According to the world health organization (WHO) records, about 9.6 million on every side of the world died from cancer in 2018 [2]. Brain cancer is dangerous, rapidly growing and is deadly. Moreover, the complexity of brain construction is a major challenge, so timely and accurate diagnosis is necessary [3]. The MRI images can provide better visualization of contrast and spatial definition. The detection of brain abnormalities process is an important issue to determine whether the abnormalities exist or not in MRI images.

The early detection of any type of disease is a key stone in the cure of patient that increases the survival possibilities [4]. This is also true in the case of brain tumor. The early detection reduces the danger on the life of patients and increases their hopes of being cured to 90%. However, early detection of the tumor is a process that involves the intervention of expert people in all evaluation process of the patient. This is costly and nearly impossible to be achieved for huge number of people. The thing that increases the importance of the use of computer aided detection of brain tumor. The CAD is a process in which the first stage of tumor detection can be achieved automatically using specialized software. The Magnetic Resonance imaging system generates the brain images while the software will be responsible to detect any

different sections or areas in the brain like tumor. The CAD will then assist the human expert in generating first report of tumor possibilities. Computer based detection can play a very significant rule in the detection of brain cancer [5].

Early detection of a brain tumor is vital since it allows for early treatment and complete recovery of patients. Recently, Computer-Aided Diagnosis (CAD) has been widely used to distinguish between benign and malignant brain tumor images. These approaches are based on MRI and CT scans used to create the images. These images show both normal and pathological brain activity. Early identification and effective treatment of illness can be improved by developing an automated classification programme that uses these images as inputs. In recent years, Convolutional Neural Networks have been routinely utilized to classify brain pictures because of their dependability. The central nervous system's most significant component is the brain. Malignant and benign tumors exist. Cancer is the medical term for a malignant tumor. The term brain tumor refers to an abnormal proliferation of cells in the brain. There are many different types of brain tumors. To benign, the majority of brain tumors originate in the brain. In this case, the tumor originates elsewhere in the body and then spreads to the brain. The cause of a brain tumor is still a mystery [6]. Medical image analysis relies heavily on segmentation for diagnosis. It breaks up the picture into its essential elements and organizes homogenous pixels into groups [7].

Segmentation in the pixel classification approach is based on feature space, which includes color components, local texture, and grey level for each pixel in the picture. The afflicted region may be separated from the remainder of the picture using image segmentation. The segmentation in this work is done through a threshold-based method [8]. Segmentation is an essential task that can be done hand-held by an expert in medical imaging. However, it provides good accuracy and a long-term process. Fully accurate and automated segmentation methods, on the other hand, are not particularly persuasive. Partially automated segmentation algorithms are acceptable for medical reasons. Hence, to overcome these time-consuming tasks, a semi-automatic segmentation method is suggested by radiologists. By using image databases, various classification techniques have been made. Besides, classification has been executed through small image databases.

Deep learning and classification are examples of computer methods. Deep learning is utilized to extract the characteristics; the classification is employed to determine whether or not the patient has a tumor [9]. Computerized imaging tools, such as MRI, CT, and X-rays, can be used to diagnose this condition. When compared to other imaging methods, MRI produces different pictures. The most promising advantage of employing traditional image processing is that it eliminates the necessity for deep learning feature extraction. When compared to traditional approaches, CNN technology exhibits better accuracy in pattern detection and picture categorization. The capacity of CNN to recognize the critical paradigm and information from the training pictures is its most important feature. In the same way, AlexNet, VGGNet, and GoogleNet are used for categorization. These are promising image classification structures that can be utilized to detect brain abnormalities in medical imaging.

2. LITERATURE REVIEW

By cause of the information mentioned above, early detection and classification of brain tumors turn into a vital task in case assessment and accordingly help in selecting the most convenient treatment method to save patients life. Furthermore, the classification stage may be a confusing and tedious task for physicians or radiologists in some complicated cases. These cases need experts to work on, localize the tumor, compare tumor tissues with adjacent regions, and apply filters on the image if necessary; to make it more clearly for human vision, and finally conclude; whether it is a tumor besides its type and grade if available. This task relatively consumes time, and that's why there is a need for a Computer Aided Diagnosis (CAD) system to early detect brain tumors in much less time without human intervention.

Machine Learning (ML) is the study of algorithms and statistical models that can be used to perform a specific task without using outright instructions, relying on patterns instead of that. ML algorithms have been widely emerged in the medical imaging field as a part of artificial intelligence. It can be divided into two main categories, supervised and unsupervised. In supervised techniques, an algorithm is used to find a mapping function of input variables and their related output labels to predict new subjects' labels. The primary goal is to learn inherent patterns within the training data using algorithms such as Artificial Neural Network (ANN), Support

Vector Machine (SVM), and K-Nearest Neighbors (KNN). In contrast, unsupervised learning is based only on the input variables as in fuzzy c-means and Self-Organization Map (SOM). There is a must to extract features of the training images that are usually grayscale, texture and statistical features to establish learning and that perhaps require segmenting the tumor in most cases before features extraction stage. These features are called handcrafted features in which an expert who has a strong knowledge and the ability to figure the most meaningful features is needed. Moreover, this job consumes much time and is prone to error while handling large scale of data.

Deep Learning (DL) is a subdivision of ML that is based on learning data representations and hierarchical feature learning. DL algorithms utilize arrange of numerous layers of nonlinear processing identities for feature extraction. The output of each sequential layer is the input of the next one, and that helps in data abstraction as we go deep within the network. Convolutional Neural Network (CNN) is a class of DL and commonly used in analyzing visual imagery and designed to require minimal preprocessing. It is inspired by biological processes in human brain and utilized to handle data that come in multiple arrays. The first use of the deep convolutional neural network with a similar form of its current one was in the recent years of the last century when Lecun introduced a deep neural network ‘‘lenet’’ that was used in document recognition applications in 1998. After many years it became much more popular right after using a deep convolutional neural network to classify images of (ImageNet LSVRC-2010), by utilizing a model called (AlexNet). AlexNet shows outstanding results in comparison with other used network structures at this period. Afterward, its success led to initiate consecutive successes of CNNs in the deep learning community.

Vishnuvarthanan et al. [10] presented a method for brain tumors detection using a novel self-organizing map (SOM) and fuzzy k-mean (FKM). Their segments results have been validated by experienced radiologists. However, their proposed approach is complex and time consuming with real practical applications.

Dhanachandra et al. [11] proposed a technique to improve MRI images quality. Their technique computes the initial value of cluster centers with helping of a subjective algorithm. They used another contrast stretching algorithm to enhance the

input image quality. They also used K-mean algorithm in their classification process, but still, there're lack of classification accuracy.

Varuna Shree and Kumar [12] used discrete wavelet transform (WDT) based on brain abnormal region. They explored a probabilistic neural network (PNN) to detect brain tumors in the MRI images.

Sachdeva et al. [13] proposed a principal component analysis-artificial neural network (PCA- ANN) for several classed brain tumor classification. They get a number of regions of interest (ROIs) by the content-based contour (CBAC). Their experiments results showed respectable enhance in the accuracy from 77% without PCA to 91% with PCA.

Corso et al. [14] proposed an automatic segmentation approach by combining a generative model-based technique and a graph-based affinities method. Their model was inserted into multi-level segmentation using a weighted aggregation algorithm.

Dong et al. [15] proposed an approach to detect brain tumors using the U_Net-based deep convolutional neural network. Their method consists of encoding and decoding, which allowed them to efficiently train their model by performing a set of data augmentation approaches.

Soltaninejad et al. [16] proposed a super-pixel approach for segmenting and automated detection for brain tumors based on a minimum redundancy maximum relevance (MRMR), extremely randomized tree (ERT) and SVM.

Al-Saffar and Yildirim [17] proposed a hybrid approach based on multiple eigenvalues selection (MES) to automate the detection of brain tumors in the MRI images. Their approach scored 91.02% in the accuracy metric.

Sultan et al. [18] suggested a convolutional neural network (CNN) founded on DL to categories distinct brain cancers utilizing two public datasets.This outcome demonstrated the model's capacity to achieve the goal of tumor multi-classification.

Maruthamuthu [19] used Spectral clustering to separate the tissues of brain tumors using Magnetic Resonance Images (MRI) to create high-standard clusters. This clustering approach has the disadvantage of requiring a large amount of data to

create dense similarity matrices. The author proposed brain tumor segmentation as a solution to this problem. This method outperformed existing clustering algorithms using competitive dice score values from MRI images for edema and TC segmentation (Tumor Core).

Gumaei et al. [20] recommended combining a hybrid feature extraction method with a regularized extreme learning machine to developing the precise brain tumor classification strategy. The tumor kind was classified using RELM (regularized extreme learning machine). The submitted work was more efficient than previous methodologies, according to the findings.

Mallick et al. [21] utilized a Deep Wavelet Auto-encoder (DWA) for picture reduction. It was a mix of the auto-encoder, a fundamental feature reduction property, and the wavelet transform, an image decomposition technique. A DWA-DNN image classifier was used to create a brain imaging dataset.

Naser and Deen [22] proposed a CNN-based U-net. It was beneficial for segmenting the tumor, and transfer learning relies on a Vgg16 pre-trained convolutional base, and a fully connected classifier was created to grade the tumor.

Kumar and Mankame [23] introduced the Dolphin-SCA deep learning method, which is based on deep CNN. It comes in handy when we need to make quick categorization judgments and enhance accuracy. Dolphin-SCA (Dolphin Echolocation based Sine Cosine Algorithm) and the fuzzy deformable fusion model were used to complete the segmentation procedure. Feature extraction was carried out using Power LDP and statistical characteristics (skewness, mean, and variance). The collected features were used in the Deep Convolution Neural Network to perform the brain tumor classification using Dolphin-SCA (as the training method) (Deep CNN).

Maheswari et al. [24], a hybrid clustering approach was introduced by. The k-means algorithm and the fuzzy c-means algorithm have been used to segment brain tumors. The method has been tested on synthetic and real-time datasets. When compared to other procedures, our strategy was more accurate.

Zhou et al. [25] started the architecture for segmenting tumors. The 3D deep supervision approach was used to improve the training.

Chen et al. [26] used a deep convolutional neural network to automatically portion brain tumors. DCSNN achieves this by casting symmetric masks in several layers (Deep Convolutional Symmetric Neural Network). Its improved segmentation networks are based on DCNN. The dice similarity coefficient metric was used to calculate the results (DSC).

The main advantages of CNNs are feature learning and providing unlimited accuracy rather than traditional machine learning and vanilla neural networks which may be achieved by increasing training samples and therefore leads to a more robust and accurate model. In CNN architecture, the convolutional filters are acting as features extractors, and as we go deep, we extract more and more complex features (spatial and structural information). Feature extraction happens through convolving small filters with the input patterns followed by selection of the most distinguishing features and then start to train the classification network.

According to a thorough review of the literature, the suggested model is built on a hybrid deep learning method. From the above literature survey, the problems identified are; for enhancing the accuracy of the segmentation, various ROI features should be extracted with the effective feature extraction technique. The existing system should not provide an effective technique to identify the tumor at the sub-regions such as core region and enhanced region. The major drawback of the existing system is it consumes more processing time. The performance of segmentation and classification should be enhanced.

3. OBJECTIVES OF THE WORK

The main objectives of this research work are

- To propose an automatic approach for brain tumor classification in order to aid the radiologists and physicians in order to identify the type of brain tumors
- To exposure and classification of the brain tumor using novel methods of segmentation techniques and classifiers.
- To improve the robustness to noise a fast and robust FCM (FRFCM), has been used to improve the performance of the segmentation and noise reduction from MRI images

- To improve the quality of the image in terms of contrast and brightness, an Edge Preservation-Contrast Limited Adaptive Histogram Equalization (EP-CLAHE) is proposed.
- To improve the accurate feature selection a hybrid Adaptive Black widow optimization with Moth Flame optimization (HABWMFO) is introduced.
- Hybrid SNK classifier is implemented in the proposed methodology for categorizing the type of tumefaction in the brain
- To develop a new hybrid deep learning model using CNN-LSTM and CNN-GRU for effective diagnosis of brain tumor

4. RESEARCH PROBLEM

To diagnose a patient with a brain tumor, radiologists use one of two techniques, invasive or noninvasive. Noninvasive techniques are the most widely used one for this purpose and can be implemented using medical imaging modalities like Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRI), etc. MRI scan is the most common modalities that are exploited to diagnose tumors in the brain. Usually, radiologists depend on manual diagnosis to detect, segment and identify brain tumors. The manual diagnosis has some drawbacks that diminish its usage in clinical applications. These drawbacks include the fact that the amount of MRI images analyzed is large enough to make readings based on visual interpretation expensive, inaccurate, and intensive. In addition, the human eye is sensitive to any changes in the MRI image; this sensitivity may be decreased with the increase in the number of MRI slices. Furthermore, manual diagnosis is time consuming, and it depends on the subjective decisions of the radiologists which is hard to quantify. These subjective decisions may lead to misclassification.

The second option for radiologists is to use invasive techniques such as biopsy and spinal tap method. In a biopsy, the surgeon penetrates the skull with a needle and takes a sample of tissue from the affected area of the brain for examination. On the other hand, in spinal tap technique, the sample is taken from cerebrospinal fluid (CSF). Both of these techniques are painful, time consuming, risky, and expensive.

5. CONTRIBUTIONS

In this research work takes advantage of a deep learning algorithm to perform automatic classification of MRI brain images.

- An image enhancement strategy employing EP-CLAHE has been suggested to improve classification results.
- To reduce noise and blurring, the preprocessing stage employs an improved Adaptive Median Filter and an Adaptive Bilateral Filter.
- An interactive segmentation process using an Adaptive Segmentation Algorithm based on modified similarity-based merging for improved accuracy is given in Figure 1.

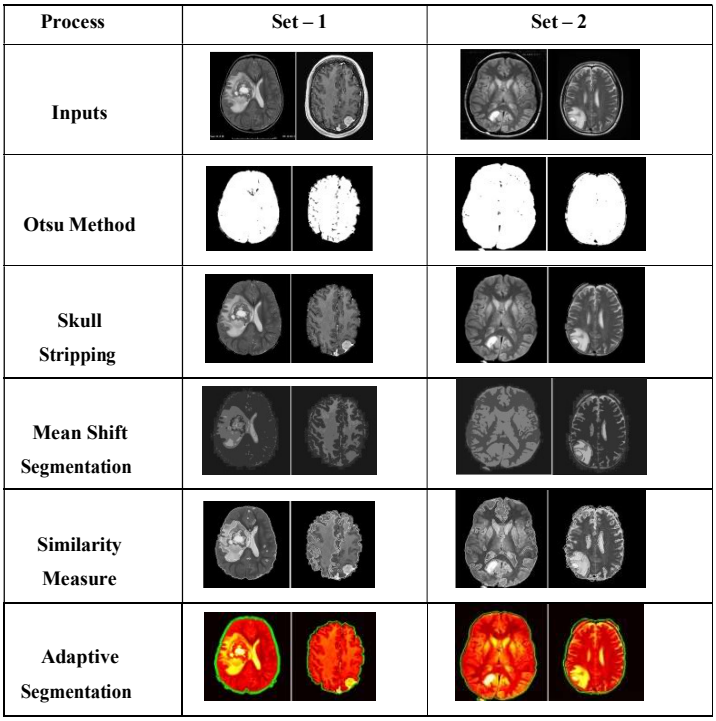

Figure 1. Sample result from Adaptive Segmentation Algorithm.

- Stationary wavelet packet transform (SWPT) is applied for the feature extraction process. To select the best features a hybrid of the Adaptive Black widow optimization with Moth Flame optimization is introduced.
- For the segmentation procedure, an Adaptive Kernel Fuzzy C Means method is used to conduct an effective clustering process
- A new hybrid hierarchical segmentation algorithm is implemented by combining Adaptively Regularized Kernel-Based Fuzzy C-Means (ARKFCM) and Morphological methods and their sample results are shown in Figure 2.

The incorporation of a couple of high–speed segmentation techniques in the proposed methodology will assist to attain better accuracy during the classification stage

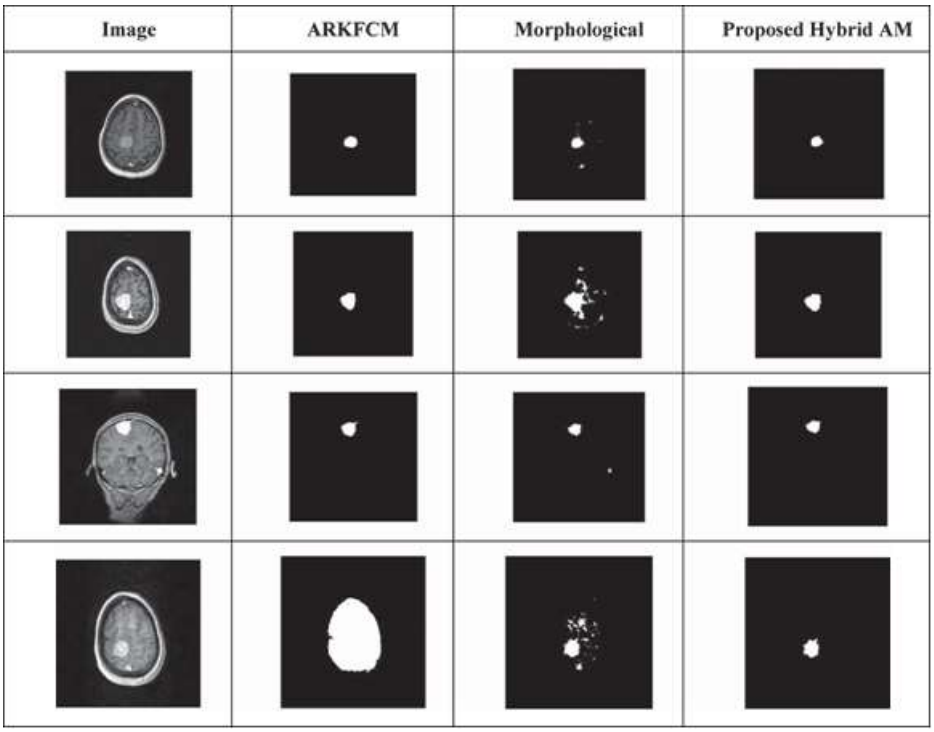

Figure 2. Sample result from Hybrid AM Method.

- Statistical, shape, and texture features are utilized to calibrate the value of the deviation of tumors. The optimal feature selection in the proposed methodology reduces the classification error and processing time
- A new weighted hybrid SNK fusion classifier can be endorsed which is of the hybridized form of SVM, NB, and KNN (SNK) classifier. It employed to combine the observations of every individual classifier
- Proposition of a hybrid deep learning model based on convolutional neural network (CNN) and gated recurrent unit (LSTM) for diagnosing brain tumor from MRI Images
- Proposition of a hybrid deep learning model based on convolutional neural network (CNN) and gated recurrent unit GRU) for diagnosing brain tumor from MRI Images
- To overcome the weight vanishing problem with limited data, we used a GRU for classification

- The performance of hybrid CNN-GRU model is compared with baseline DL models VGG16, VGG19, hybrid CNN-LSTM and SNK-SVM in the Figure 3. Results show that the hybrid CNN-GRU model significantly improves accuracy compared to the baseline models.

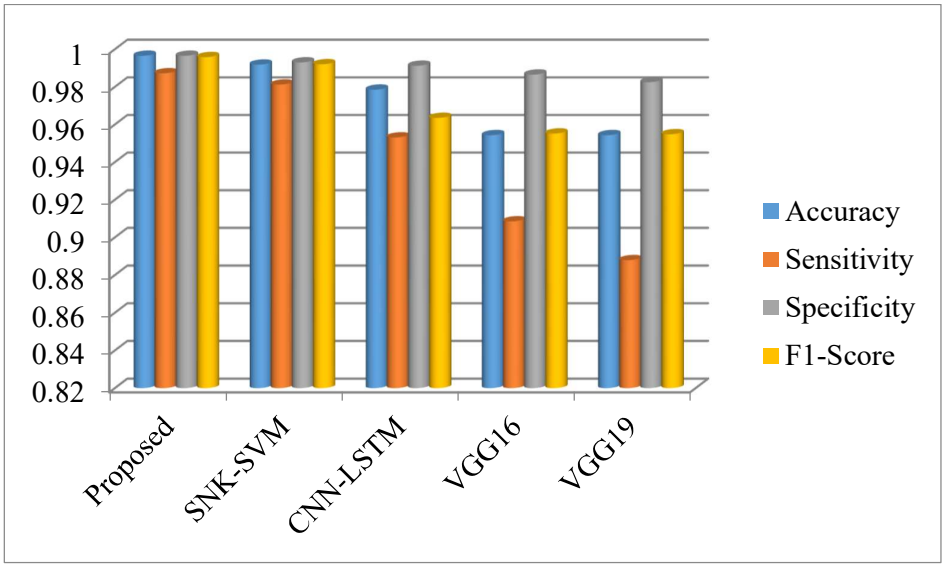

Figure 3. Comparison between the explored models and the Hybrid CNN-GRU

- We evaluate the proposed approach using a new public dataset of brain images and compare with the state-of the-art approaches on the same dataset.

6. ORGANIZATION OF THE THESIS

The research work is organized into four chapters and is as follows:

Chapter 1

This chapter covers the types of brain tumor, the disease rate and the average survival rate. Also it explains about the fundamental concepts of segmentation, feature extraction and classification of brain tumor. We discuss the importance of deep learning methods, as well as the thesis motivation, objectives, contributions, and organization.

Chapter 2

This chapter articulates on the associated research findings about various segmentation and optimization methods. Furthermore, it elaborates on the various

technical contexts of the deep learning techniques we are considering in order to achieve the better performance.

Chapter 3

This chapter discusses the process of brain tumor classification using adaptive segmentation algorithm. It highlights the idea about skull stripping is the preprocessing method used for the removal of non – brain tissues, ASA process is implemented to select the adjacent tissue with respect to the intensity of the channel and label posteriors, Gaussian Inception (GI) is employed to extract the features from the input MR images with reduced loss. Some of the features like mean, entropy, energy, standard deviation are extracted for the classification. The number of input samples is classifier under SVM classifier. Experimental results show that the accuracy is greatly improved in contrast with the existing work in brain MRI.

Chapter 4

In this chapter, a new hybridized method for brain tumor segmentation and classification is discussed. The main characteristics are: an efficient hierarchical segmentation scheme suitable for the resource-constrained platform and a new set of multi-features using first-order and second-order statistical features, shape features, and texture features. These multi-features efficiently capture the variation of brain image and a new mechanism of a Hybrid SNK classifier has been implemented to classify the SNK classifier has been implemented to classify the brain image. Finally, the classifier is built for each feature category and then the final results are obtained. The results manifest that the accuracy of the Hybrid AM segmentation method is far better than existing ARKFCM and Morphological methods. Besides, the classification results demonstrate that the proposed Hybrid SNK classifier attained high classification rates compared with the existing state of-the-art classifiers.

Chapter 5

In this chapter, a hybrid deep learning-based brain tumor diagnosis and classification is discussed. Stationary wavelet packet transform (SWPT) is applied for the feature extraction process. Then, a hybrid Adaptive Black widow optimization

with Moth Flame optimization (HABWMFO) is utilized for the optimal feature selection. Following that, the feature values are being sent to clustering for segmentation. For segmentation, the Adaptive Kernel Fuzzy C Means clustering technique (AKFCM) was developed. Finally, a Hybrid Convolution Neural Network-Long Short-Term Memory (CNN-LSTM) deep learning is used to improve tumor classification accuracy. Experimental result shows that the performance of the CNN-LSTM is improved by using a hybrid ABWO-MF. Different performance parameters that are used to estimate performance

Chapter 6

This chapter explains the design methodology of hybrid deep learning model based on a convolutional neural network (CNN) and gated recurrent unit (GRU). The brain tumors are classified using CNN-GRU. CNN is used as a feature extractor and GRU as a classifier. Furthermore, the performance of hybrid CNN-GRU model are compared with hybrid CNN-LSTM and also with different baseline models such as VGG16, VGG19, hybrid CNN-LSTM and SNK-SVM. The results show that the hybrid CNN-GRU outperformed all other models in terms of accuracy.

Chapter 7

This chapter specifies the concluding research contributions and future research perspectives.

8. CONCLUSION

In this research, few investigations on brain tumor detection in MRI images is performed to develop an automated diagnosis system. The automated system is developed on the traditional procedure such as pre-processing, segmentation, feature extraction and classification. For segmentation, Adaptive segmentation Algorithm (ASA) and Adaptive Kernel Fuzzy C Means clustering technique (AKFCM) are used. Then, a hybrid Adaptive Black widow optimization with Moth Flame optimization (HABWMFO) is utilized for the optimal feature selection. The feature values are supplied into the clustering algorithm for segmentation after picking the best features. Furthermore, we have introduced few classification methods like Support Vector Machine (SVM), Hybrid SNK, CNN-LSTM and CNN-GRU. The results show that the hybrid CNN-GRU outperformed all other models in terms of accuracy

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